Assessing the probability of human injury during UV-C treatment of crops by robots

Leonardo Guevara, Muhammad Khalid, Marc Hanheide and Simon Parsons
Lincoln Centre for Autonomous Systems,
University of Lincoln, UK
{lguevara, mkhalid, mhanheide, sparsons}@lincoln.ac.uk

***Abstract*—This paper describes a hazard analysis for an agricultural scenario where a crop is treated by a robot using UV-C light. Although human-robot interactions are not expected, it may be the case that unauthorized people approach the robot while it is operating. These potential human-robot interactions have been identified and modeled as Markov Decision Processes (MDP) and tested in the model checking tool PRISM.**

***Index Terms*—agricultural robotics, UV-C treatment, hazard analysis, human-aware navigation, model checking**

I. Introduction

In commercial growing operations, crops are sprayed with various pesticides in order to keep diseases at bay. To help reduce the use of chemicals, our collaborators at SAGA robotics have developed a robot that can dose strawberry plants with UV-C light to treat powdery mildew. The robot configuration used during the UV-C treatment is presented in Fig.1, where the robot straddles the tables on which the strawberries grow so that the UV-C emissions are directed inwards. The UV-C dose is carefully calibrated to not damage the strawberry plants but it can harm any other living thing that come closer than 7m to the robot. Thus, even though human-robot interaction during the UV-C treatment is unlikely, it is always possible that an untrained human decides to approach the robot to have a look. For these situations it is crucial that the robot incorporates an on-board safety system with the aim of detecting the approach of a human, alerting the human of the danger and stopping operations if it is required.

In this context, this paper summarizes the potential risks and failure modes identified during a hazard analysis of the UV-C treatment scenario. These failures are then used to construct a model of the human-robot interaction which can be translated into a Markov Decision Process (MDP) to be tested by the PRISM model checking tool [2]. Some preliminary results assessing human injuries are given, pointing some important safety requirements that must be considered during the design and validation of a safety system architecture for the robot.

II. Methodology

A. Hazard identification

For the hazard analysis, we followed the systematic technique called Failure Mode and Effects Analysis (FMEA) [3], which involves identifying and evaluating potential hazards in a system, their occurrence frequency, and determining the severity of the consequences. [4]. In this context, Table I gives a list with the three main risk situations that may occur during UV-C treatment according to a cognitive walkthrough. The consequences of identified failures correspond to potential injuries from UV-C light (F2 and F3), and the risk that people are not getting aware of the danger and continue approaching (F1 and F4) which later contribute to the F2 and F3 occurrence.

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Fig. 1: The robot configuration for the UV-C treatment.

B. Safety requirements

The hazard identification is used as input for a Functional Hazard Analysis (FHA) in order to define safety requirements which reduce the severity and/or occurrence of the failures F1-4 described in Table I. In our case, the following two requirements were proposed:

SR1: The robots must incorporate an Audiovisual Alert System (AAS) to signal their current behavior and potential danger. The alerts are triggered any time a human is detected (hopefully above 7m), but also are programmed to be activated periodically in case a human was not detected on time.

SR2: The robots must implement a robust Human Detection System (HDS) based on LiDARs and/or cameras that can detect human presence above 7m. In this way, the robot can stop operations before the human get closer than 7m.

III. Preliminary Results

A. Modelling

The human-robot interactions during UV-C treatment and the behavior of the safety systems (i.e HDS and AAS), were modeled as Markov Decision Processes (MDP) in which the

TABLE I: List of possible risky situations and failure modes during UV-C treatment.

Possible situations	Code	Possible failures	Potential effect	Consequence	Severity	Ocurrence
Robot moving along the row while a human is approaching frontally	F1	Robot fails to detect human farther than 7m	Robot audiovisual alerts are not activated	Human is still approaching to the robot	critical	occasional
	F2	Robot fails to detect human closer than 7m	Robot safety stop is not activated	Human is injuried by the UV-C light	catastrophic	occasional
Robot at the end of the row while a human is approaching laterally	F3	Robot is aware of the human presence only when they are too close	Robot safety stop is not activated	Human is injuried by the UV-C light	catastrophic	probable
Robot detects a human and activate audiovisual alerts	F4	Human was not trained to interpret the alerts	Human is not getting aware of the danger	Human is still approaching to the robot	marginal	remote

transition between states is non-deterministic and modeled by probability distributions. To implement the MDP model in PRISM, a single module was created with 5 local variables which define the states of the robot, human, HDS, and AAS. Ten constants were used to define the transition probabilities of the human decisions, and to characterize the effectiveness of HDS beyond 7m and the effectiveness of the AAS to make the human aware of the danger. Additional auxiliary variables were used to synchronize the transition of states in a specific order. Full details may be found in [1].

B. Model checking

The MDP was analyzed through model checking. Figure 2 gives preliminary results showing how the probability of human injury varies according to the occurrence of failures F1-4. During the experiments, the probability of each failure was varied from 0 to 1 while keeping the probability of remaining failures constant at 0.1 (i.e. failures are always present, but the aim is to analyze which failure influences the most on human injuries). In all the plots, the potential human injuries were also evaluated according to the probability of a human deciding to approach the robot. This probability was varied from 0 to 1 and is shown on the x-axis as the probability of human-robot interaction. The riskiest situation is shown in Fig. 2(c) where, under the assumption that the robot is completely unaware of the human when they approach from the side, the probability of injury is 0.52. The remaining plots showed a much lower chance of injury, with the probability of human injury being less than 0.1. These preliminary results suggest that more effort should be put on robustify the HDS when the robot is at the end of the rows than where the robot is moving along the row. Moreover, pre-programmed explicit voice messages may be activated each time the robot is going to leave a row in order to get the human (trained or not) aware of the robot presence on time.

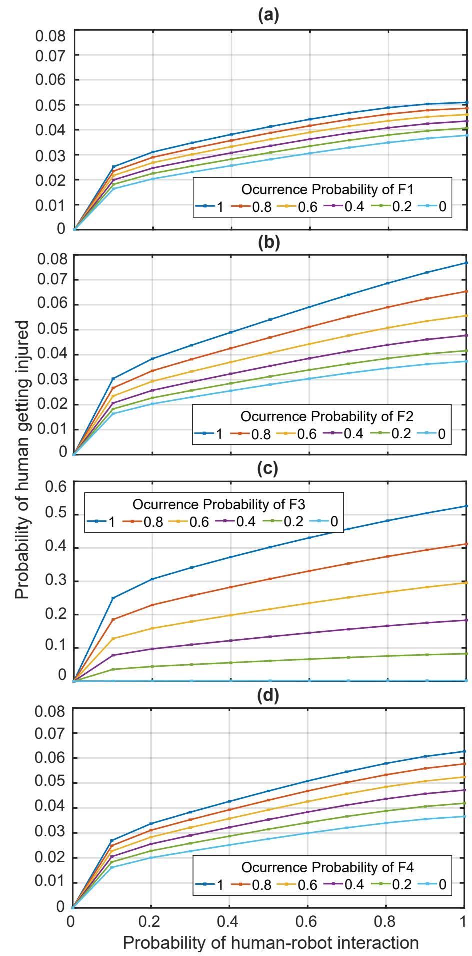

Fig. 2: Probability of a human getting injured by the UV-C light when varying the occurrence probability of a) F1 b) F2 c) F3 d) F4. The three remaining failures which are not analyzed on each case are assumed with a fixed occurrence of 0.1.

IV. Conclusions

This paper presented a preliminary assessment of potential human injuries during UV-C treatment operations. Based on the failures identified during a traditional hazard analysis, we have constructed a probabilistic model to evaluate the effectiveness of any proposed safety systems. The results of the model checking gives the user guidelines on how to improve the current safety systems effectiveness either through improving detection algorithms, adding new sensors to overcome possible hardware limitations, or by including new safety policies related to the workspace.

References

[1] L. Guevara. Probabilistic modelling and formal verification using PRISM; As case study in agricultural robotics. Technical report, School of Computer Science, University of Lincoln, 2021.

[2] M. Kwiatkowska, G. Norman, and D. Parker. PRISM 4.0: Verification of probabilistic real-time systems. In G. Gopalakrishnan and S. Qadeer, editors, *Proc. 23rd International Conference on Computer Aided Verification (CAV'11)*, volume 6806 of *LNCS*, pages 585–591. Springer, 2011.

[3] Diomidis H Stamatis. *Failure mode and effect analysis: FMEA from theory to execution*. Quality Press, 2003.

[4] Roger Woodman, Alan F.T. Winfield, Chris Harper, and Mike Fraser. Building safer robots: Safety driven control. *The International Journal of Robotics Research*, 31(13):1603–1626, 2012.